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Mining Learning Preferences in Web-based Instruction: Holists vs. Serialists

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ABSTRACT

Web-based instruction programs are used by learners with diverse knowledge, skills and needs. These differences determine their preferences for the design of Web-based instruction programs and ultimately influence learners' success in using them. Cognitive style has been found to significantly affect learners' preferences of web-based instruction programs. However, the majority of previous studies focus on Field Dependence/Independence. Pask's Holist/Serialist dimension has conceptual links with Field Dependence/Independence but it is left mostly unstudied. Therefore, this study focuses on identifying how this dimension of cognitive style affects learner preferences of Web-based instruction programs. A data mining approach is used to illustrate the difference in preferences between Holists and Serialists. The findings show that there are clear differences in regard to content presentation and navigation support. A set of design features were then produced to help designers incorporate cognitive styles into the development of Web-based instruction programs to ensure that they can accommodate learners' different preferences.

Keywords

Learning preferences, Holist, Serialist, Pask, Field Dependence, Field Independence

Introduction

The World Wide Web (Web) provides an extremely large and dynamic information resource (Ma, Pant, and Sheng, 2007) and is currently being applied extensively as an important means for information dissemination (Harumoto, et al., 2005). In other words, using the Web has become an essential part of our daily life (Kirkwood, 2008). In particular, Web-based Instruction (WBI) has become increasingly popular in educational settings (Brotherton and Abowd 2004). Due to such popularity, WBI programs are used by many different students, each of which has their own set of personal preferences because they have different backgrounds, knowledge, and skills. In other words, human factors, namely those individual characteristics that can potentially affect the design of human-computer interaction (Sears and Jacko, 2009), are a necessary consideration in the design of WBI programs. There are many human factors, such as cognitive styles (e.g., Chen and Macredie, 2004), gender differences (e.g., Roy and Chi, 2003) and prior knowledge (e.g., Mitchell, Chen, and Macredie, 2005). Among them, cognitive style, which describes and explains differences in the preferred strategies for information representation and processing among individuals (Riding and Rayner, 1998), is particularly widely studied in the area of WBI because it has been shown to have a great effect on learners' preferences (Ford and Chen, 2001). The most widely studied cognitive style dimension is that of Witkin's (1976) Field Dependence/Independence. As showed in previous studies (e.g. Chen and Macredie, 2004; Chen and Liu, 2008), the Field Dependence/Independence dimension has considerable effects on learners' preferences for the design of WBI.

On the other hand, Pask's (1979) Holist/Serialist dimension has conceptual links to the Field Dependent/Independent dimension and such links suggest that this dimension of cognitive style may also play an influential role in the design of WBI programs. As suggested by Ford (2000), the Holist/Serialist dimension has potential for adapting computing-based systems to the needs of each learner. However, previous literature has paid less attention to this dimension of cognitive style. Thus, there is a need to examine how the Holist/Serialist dimension affects learners' preferences for the design of WBI programs. To this end, the study presented in this paper will investigate the influence of this particular cognitive style dimension on learners' preferences for the design of WBI programs.

Furthermore, this study will apply data mining techniques to analyze the relationship between learners' cognitive styles and the influence this has on their preferences for WBI programs because our previous work shows that employing the use of data mining techniques can help to identify relationships that were previously hidden by statistical analyses (e.g. Chen and Liu, 2008). Unlike our previous work, we, however, use multiple data mining techniques. Firstly, two families of classifiers are used to select relevant features and then three types of decision trees are applied to illustrate learners' preferences. With such an approach, this study will not only contribute to the understanding of how Pask's (1979) Holist/Serialist dimension influences learners' preferences, but also propose a new way to conduct data analyses

In this vein, this paper begins by analyzing previous research relating to WBI and cognitive styles and continues by providing a background on the data mining techniques used in this study. The methodology used to conduct the empirical study is described in section 3, followed by the discussion of the findings in section 4. This section also suggests a set of design points drawn from the findings that should be included in an interface to account for learners' cognitive styles. Conclusions are then presented in section 5 where suggestions for future work are also proposed.

Related Works

Web-Based Instruction

Web-based instruction (WBI) programs provide flexible teaching and learning environments for students through the provision of non-linear learning (Pituch & Lee, 2006), as students have the freedom to control their learning by themselves, for example, through the use of different navigational tools. Due to such freedom, WBI programs are very attractive to students. With the expanding usage of such programs, the ability to effectively match the interface design with the increased diversity in students' preferences becomes vital to their success. Thus, there is a need to examine the influences of human factors, among a variety of which cognitive style has been identified as one of the most pertinent factors because it refers to a person's information processing habits, representing an individual's typical mode of perceiving, thinking, remembering, and problem solving (Messick 1976). It has also been suggested that matching cognitive styles to the design of WBI programs can lead to better learning performance (Ford and Chen, 2001).

In particular, previous studies found that Witkin's (1976) Field Dependence/Independence affects how students react to WBI programs. For example, Lu, Yu, and Liu (2003) found that Field Dependent learners used the teaching notes and class resources more than Field Independent learners. Lee et al (2009) found that Field Independent learners used the back/forward buttons more frequently and spent less time on navigation than their Field Dependent counterparts. Additionally, Field Dependent users were found to use the main menu more often and had more repeated visits. Chen and Liu (2008) found that Field Independent learners preferred to use the alphabetical index whilst Field Dependent learners preferred the hierarchical map. These clear differences permit designers to accommodate these preferences in interface designs, allowing for more effective use of WBI.

Table 1: Differences between Holist and Serialist characteristics (Pask, 1979)

Holists	Serialists
• Take a global approach and create conceptual links between objects early on.	• Take an analytical approach, examining individual topics before forming conceptual links.
• Are able to move between theory and real world examples from the beginning.	• Analyzes theory or real world examples separately, only joining together if necessary.
• Broad focus; likes to have more than one thing on the go at the same time.	• Narrow focus; prefers to focus on completing one task before moving on to the next.
• Internally directed.	• Externally directed.

In addition to the Field Independence/Dependence cognitive style dimension, another dimension of cognitive style, i.e., Pask's Holist/Serialist (1979), was also found to be an influential factor to student learning. According to Pask's description, Holists will adopt a style termed comprehension learning which involves building descriptions of what is known whereas the Serialists will adopt a style termed operation learning which is concerned with the mastering of procedural details (Pask, 1979). Additionally, Jonassen and Grabowski (1993) describe the Holists as preferring to process information in a 'whole-to-part' sequence. In contrast, Serialists are described as preferring a 'part-to-whole' processing of information. As shown in Ford's study (1993), Holists strongly favored a global picture by using a map. On the other hand, Serialists preferred to use an index to access information. A detailed comparison of the differences between Holists and Serialists preferences can be seen in Table 1.

As shown in this Table, Holists will prefer to adopt a global approach and focus on piecing together a broad conceptual overview before then looking further to fit other details in, whereas Serialists prefer to use a local approach, examining one object at a time and only then concentrating on linking objects to the building of the conceptual map (Pask, 1979). More specifically, the former develop an overall and general understanding of the scope and structure of learning tasks at hand and gradually shift attention to details that fill in the structure while the latter would tackle individual details first, connect the separate topics, and finally form the overall picture (Ford, 2000). In other words, Holists share similar characteristics to those of Field Dependent users, who tend to emphasize on an overall picture of the subject content. Conversely, Serialists are like Field Independent users, who tend to build up procedural understanding step-by-step. In summary, these two dimensions of cognitive style have some similarities, but Pask's Holist/Serialist (1979) is rarely examined in the area of WBI. To address this issue, this dimension of cognitive style is considered in this study. Unlike most of previous studies which used traditional statistics to analyze data, a data mining approach is applied in this study because it can discover hidden patterns (Chen and Liu, 2008).

Data Mining

Although data mining techniques are more traditionally applied in the areas of Bioinformatics or E-Business, there is an increasing interest in applying these techniques in educational settings with the aim of gaining a deeper understanding of students and their learning environments (Romero and Ventura, 2007). Lack of a deep and sufficient understanding in e-learning systems may prevent to deliver high-quality services, but data mining is helpful to bridge this gap (Ayesha, et al., 2010). Thus, some research attempted to use data mining techniques to e-learning systems, including personalizing distance education courses and e-text books (Romero and Ventura, 2007). For instance, Tang et al. (2000) constructed a personalized web tutor tree by using a key-word-driven text mining algorithm to select articles for distance learning students. Additionally, Chen, Li, Wang, and Jia (2005) used web content mining to develop an e-textbook where a ranking strategy was employed to evaluate the web page suitability and to extract concept features and build concept hierarchies.

These works demonstrate that data mining is advantageous to automatically model learners' preferences. However, the analysis of the relationship between cognitive styles and the corresponding user preferences for WBI programs has mainly been investigated through statistical analyses (e.g. Graff, 2003), which require assumptions to be made beforehand, introducing bias if these assumptions are not entirely accurate. In contrast, data mining is discovery driven so there is no need to have any assumptions in advance (Romero and Ventura, 2007). More specifically, data mining is the search for valuable information within large volumes of data (Hand, Mannila, & Smyth, 2001). This valuable information can then be used to predict, model or identify interrelationships (Urtubia et al, 2007) without the need to predefine underlying relationships between dependent and independent variables (Chang and Chen, 2005). However, human preferences data is often 'noisy' and full of inaccurate information, which can lead to biased results. Therefore, a pre-processing step, such as feature selection, is necessary to sift through the data so that only the most relevant subsets are included in the mining process (Bishop, 1995).

Feature selection methods can be divided into two categories, including filters and wrappers. The former uses statistical methods to produce a ranking of features whereas the latter uses classifiers to evaluate small subsets based on the interactions between features (Yang and Olafsson, 2006). The wrappers generally perform better than the filters (Raman and Ioerger, 2002) so the wrappers were taken into account in this study. However, the outcomes of the wrappers depend on the type of classifier used. For example, Bayesian Networks and Nearest Neighbour are two of the most popular families of classifiers. Classifiers from these families have different architectures and therefore have different biases associated with them. For example, Bayesian Network classifiers focus on features that maximize/minimize a scoring metric whereas those from the Nearest Neighbour family focus on features that are deemed the 'closest' by an imposed distance metric (Huan and Lei, 2005). This study addresses attempts to overcome this issue by comparing the accuracy of feature sets obtained using classifiers from various families, instead of choosing just one classifier or one family.

After the data has been pre-processed and contains only the most relevant features, classification, which is a data mining technique that uses algorithms to find models that describe a data class or concept (Han and Kamber, 2006), can be used to model the preferences of different types of learners. One of the most popular classification tools are decision trees, which are employed to discover rules and relationships by systematically dividing information contained within data (Chen, Hsu and Chou, 2003). Data is classified by constructing tree-like structures through a series of Boolean functions, yes/no questions based on the characteristics of a set of variables, until a pre-defined level is reached. Thus, the hierarchical structure created can help researchers easily understand hidden relationships within the dataset (Lee et al, 2009). Decision trees have been widely used to classify user preferences. For example, Liu and Kešelj (2007) used decision trees to classify users' Web navigational patterns with the aim of predicting which pages were more likely to be visited next.

Due to the success of decision trees in such studies, this study will use decision trees to illustrate the differences in preferences between Holists and Serialists. A review of existing literature shows that the most widely used decision tree algorithms include Classification and Regression Trees (CART, Breiman et al., 1984), C4.5 (Quinlan, 1993) and CN2 (Clark and Nibbet, 1989). A difference amongst these three algorithms is the process of model development. C4.5 algorithms split a tree model into as many results as necessary whereas the CART algorithm can only support binary splits. Unlike CART and C4.5, CN2 is a rule based algorithm that produces an ordered list of IF-THEN rules that can be visually demonstrated on a decision tree. Due to these differences, using a single decision tree may cause some biases. Thus, all of these three algorithms will be applied in this study and then we use the one which produces the highest accuracy to illustrate the different preferences of Holists and Serialists. By doing so, more reliable results can be obtained.

Methodology Design

Empirical Study

The research question examined in this study is how Holists and Serialists show different preferences to the design of a WBI program. The students from a UK university were invited to participate in the study by email. It was indicated in the email that all of the participants were requested to have the basic computing and Internet skills, e.g., the abilities of using a browser or a mouse. By doing so, they were able to interact with the WBI program used in this study. Finally, 65 students from various subject areas, including business, information science, and mathematics, volunteered to participate in this study. The sample was evenly divided between male (N=32) and female (N= 33).

The empirical study consists of the following three steps:

1) *Identification of Cognitive Styles*: The participants' cognitive styles were classified into Holist or Serialist by Ford's Study Preference Questionnaire (SPQ), which had been used in several previous studies (e.g. Ford and Chen, 2000; 2001). The SPQ is an 18-item inventory for assessing students' learning strategies. The participants were provided with two sets of statements, one on the left and the other on the right, which they were then asked to indicate their degree of agreement with either statement, or to indicate no preference (Ford, 1985). If participants agreed with over half of the statements related to Holists, they were classified as Holists. If they agreed with over half of the statements related to Serialists, they were classified as Serialists. If they agreed with an equal number of the statements related to Holists and Serialists, they were classified as Intermediate. According to these recommendations, the sample of 65 participants was evenly distributed, with 33 Holists and 32 Serialists, but there were no intermediate students.
2) *Interaction with the WBI program*: The participants were asked to explore the subject content of the WBI program for approximately 90 minutes. The subject content of the WBI emphasized on the practical skills of designing web pages, in this case, *How to use HTML*. In order to examine the preferences of different cognitive styles, the WBI program provided multiple navigational tools for each participant, including an alphabetical index, a hierarchical map, a main menu, section buttons and hypertext links within the text. Thus, the participants were given the freedom to explore the instructional material in the way preferred by them. Figure 1 illustrates the design of the WBI program.
3) *Completion of a Questionnaire*: The participants were requested to fill out a questionnaire so that their perceptions to the use of the WBI program can be identified. This instrument was chosen because it has the potential to collect cognitive and affective data quickly and easily (Kinshuk, 1996). The questionnaire was specifically used to examine the perceptions of different cognitive style groups. Therefore, we decided to design a questionnaire specifically for this study, instead of using existing questionnaire. The reliability of the questionnaire was found to be acceptable (α=0.81). The questionnaire consisted of 20 closed statements, which were designed to gathering specific quantitative information about students' comprehension, preferences, and

satisfaction or dissatisfaction with the WBI program, including content presentation; interaction styles; functionality and usability; and difficulties and problems. All statements used a five-point Likert Scale consisting of: ‘strongly agree’; ‘agree’; ‘neutral’; ‘disagree’; and ‘strongly disagree’. The participants were required to indicate agreement or disagreement with each statement, by placing a check mark at the response alternative that most closely reflected their opinion.

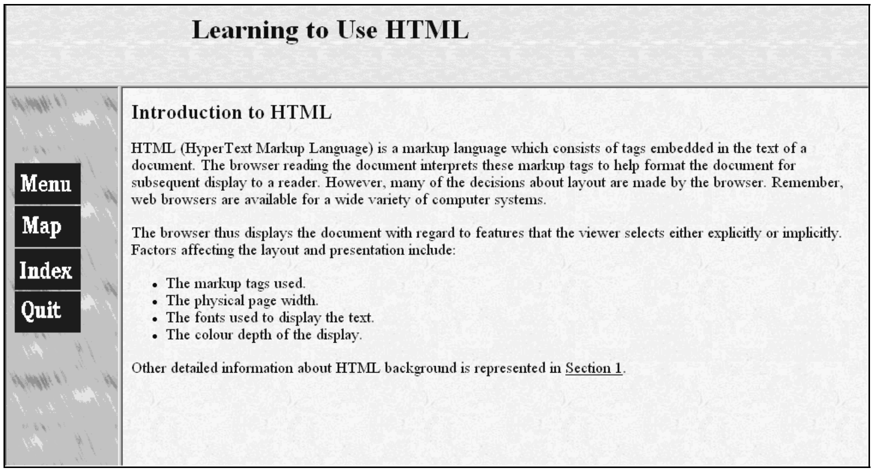

Figure 1: The WBI program

Data Analysis

This study examines how cognitive styles affect the students’ preferences for the design of the WBI program. The students’ cognitive styles were recognized as Holists and Serials with Ford’s SPQ. Their preferences were identified with a questionnaire, which included 20 statements. The responses of the statements, where appropriate, were scored as 5 for “strongly agree”, through to 1 for “strongly disagree”. As described in Introduction, data mining was applied to analyze the students’ responses to the questionnaire. The data mining process included two different stages. The first stage involved classifiers from two different families, Bayesian Networks (BN) and Nearest Neighbour (NN). These two families were chosen because of their different natures. BN use conditional probability distributions to identify the relationship between a feature and a targeted variable. On the other hand, KNN focuses on features and instances that are deemed the ‘closest’ by an imposed distance metric (Gammerman, 1997). Three of the most widely-used classifiers from each of the two classifier families were used (Table 2). These classifiers were then used to select the most relevant questions (features) from the questionnaire that were related to the Serialist/Holist cognitive style dimension.

Table 2: Two Classifier Families

Classifier Family	**Classifier**
Bayesian Networks (BN)	Bayesian Network (BNC) Naive Bayes (NB) Averaged-One-Dependent Estimates (AODE)
Nearest Neighbour (NN)	Nearest Neighbour (NNC) k-Nearest Neighbour (KNN) k-Star (K*)

In the second stage, the resulting six feature sets selected in the first stage were then used to build decision trees. Three of the most popular decision tree algorithms, including Classification and Regression Trees (CART, Breiman et al., 1984), C4.5 (Quinlan, 1993) and CN2 (Clark and Nibbet, 1989), were used to create decisions trees. They have been chosen because they are among the most popular, the most established and the best tested in previous research (e.g., Kim, et al., 2002).

To identify a reliable decision tree, cross validation was used to assess the accuracies of the decision trees produced with the aforesaid three decision tree algorithms. This is due to the fact that cross validation is a generally applicable and very useful technique for accuracy estimation of data mining tasks. In particular, it is widely applied for decision tree induction (Blockeel and Struyf, 2002). It consists of partitioning a data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the testing set). Multiple rounds of cross validation are performed using different partitions and then the accuracy results from each round are then averaged to produce the estimated accuracy. In this study, ten rounds were conducted because this value has been widely used when applying cross validation to different data mining tasks (Ruiz, Riquelme and Aguilar-Ruiz, 2006). According to the results of the cross validation, the decision tree with the highest accuracy was then used to illustrate how students' cognitive style affects their preferences for the WBI.

Results and Discussion

The following section describes the results obtained from the method described in Section 3.2. Two steps were followed to obtain these results. Firstly, six classifiers from two different families were used to produce six feature sets containing only the most relevant features to Holists/Serialists. Secondly, three different decision tree algorithms were applied to produce decision trees, among which the one with the highest accuracy was then used to illustrate the effects of cognitive styles on learners' preferences for WBI.

Feature Selection

Three classifiers each from both the Bayesian Network (BN) and Nearest Neighbour (NN) families were used to obtain six feature sets. As shown in Table 3, these six classifiers selected different sets of relevant feature. The Bayesian Network classifier (BNC) selected the fewest relevant features (n=7), whereas the Nearest Neighbour classifier (NNC) selected the most relevant features (n=13). Such results contribute to the understanding of the differences among these classifiers.

Out of the twenty original features, 19 of them were selected as relevant by one or more of the classifiers. More specifically, only Q13 ("*Too many options let me feel confused which options I wanted*") was not selected by all of the classifiers. The feature that was commonly selected as relevant by all six classifiers was Q9 ("*It is hard to use backward/forward buttons*"). Three other features, Q2 ("*Examples given in this tutorial are not practical*"), Q14 ("*After using this system I can easily use my knowledge to design home pages*") and Q18 ("*It is easy to find a route for a specific task with the index*") were also commonly selected as relevant by five out of the six classifiers. As these four features were commonly selected by the majority of classifiers, this suggests that they are the most relevant in distinguishing the preferences of Holists and Serialists. In other words, back/forward buttons, examples and indexes are important features that need to be considered in the design of WBI to ensure that the different needs of Holists and Serialists can be accommodated.

Table 3: Relevant features selected

No	Description	Bayesian Network Classifiers			Nearest Neighbour Classifiers		
		BNC	NB	AODE	NNC	KNN	K*
1	It is difficult to learn the basics of HTML using this tutorial without the help of a person.				X	X	
2	Examples given in this tutorial are not practical.	X	X	X	X		X
3	I felt the structure of this tutorial is not clear.			X			
4	I sometimes got lost because the buttons made me feel confused.					X	
5	I spent a lot of time getting to know how to use this tutorial.				X		
6	I would have found it more helpful to be given a suggested route through this tutorial.		X		X	X	X
7	I would like to have more examples.		X		X		X

8	I would prefer to learn from human tutor than from this tutorial.				X		
9	It is hard to use back/forward buttons.	X	X	X	X	X	X
10	The information provided by the map is too superficial.	X	X	X		X	
11	The links provided in this tutorial help me discover relationships between different topics			X	X		X
12	The map in this tutorial gives a meaningful framework of HTML.	X	X				
13	Too many options let me fee confused which options I wanted.						
14	After using this system I can easily use my knowledge to design home pages.	X	X		X	X	X
15	I found it hard to select relevant information using the map.	X	X	X		X	
16	I like the fact that it allowed me to learn topics in any order.	X	X	X	X		
17	I like the fact that this tutorial allowed me to work at my own pace and direction.				X		X
18	It is easy to find a route for a specific task with the index.		X	X	X	X	X
19	This tutorial can be used sufficiently well without any instructions.			X			X
20	I felt difficult to browse pages containing texts and links in the same pages.				X		X
Total		**7**	**10**	**9**	**13**	**8**	**10**

Classification

The classification stage involved two steps. Initially, three different decision tree algorithms were used to create decision trees. Secondly, the decision tree with the highest accuracy (the percentage to which how well the decision three was able to accurately predict students' cognitive styles) was employed to illustrate how cognitive style affected students' preferences for the use of WBI programs.

Finding the most accurate feature set

Three decision tree algorithms, C4.5, CART and CN2, were used to produce decision trees with the six feature sets identified in the previous stage. In order to find the most accurate decision tree, firstly the average accuracy for each algorithm was calculated (Table 4). The idea here was that it was assumed that the decision tree with the highest average accuracy would be the best one to predict the preferences of each cognitive style. Although all three algorithms produced high accuracies, CN2 is the algorithm which produced the decision trees with the highest average accuracy.

Table 4: Classification Accuracies for the Feature Sets

Feature Set	**Classification Algorithm**		
	C4.5	**CART**	**CN2**
BN	70.77	79.83	80
NB	70.77	76.79	80
AODE	67.69	87.74	80
NN	72.31	76.79	80
KNN	70.77	76.79	80
K*	70.77	76.79	80
Average Accuracy	**70.51**	**79.12**	**80**

After identifying the algorithm which can produce the decision trees with the highest average accuracy, the most accurate feature set was then identified from those classified with the CN2 algorithm. Somewhat surprisingly, CN2 classified all six feature sets with the same accuracy of 80%.

Illustrate student preferences with a decision tree

As the most accurate algorithm (CN2) classified all feature sets with the same accuracy (80%), it was necessary to examine the decision trees produced using these feature sets. Five different trees were produced, with the NN and KNN feature sets producing an identical tree (Figure 2), which probably reveals the underlying structure of the students' preferences revealed in this study. Moreover, this decision tree was found to include all of the information found by the other classifiers. Therefore, this decision tree is assumed to be the most accurate representation of preferences for all of those involved in the study. For this reason, this decision tree was chosen to illustrate the preferences of Holists and Serialists.

As showed in Figure 2, seven features are considered in the chosen tree to distinguish between the preferences of Holists and Serialists. In particular, three features illustrate this difference quite clearly: Q9, Q11 and Q6. Regarding Q9, learners that strongly agree or agree with "*It is hard to use back/forward buttons*" are classified as Holists. Conversely, Serialists show opposite opinions. Additionally, learners who strongly agree with Q11 ("*The links provided in this tutorial help me discover relationships between different topics*") are classified as Holists and those who strongly disagree with this are classified as Serialists. Furthermore, those users who strongly disagree with Q6 ("*I would have found it more helpful to be given a suggested route through this tutorial*") are classified as Holists whereas those that agree with this are classified as Serialists.

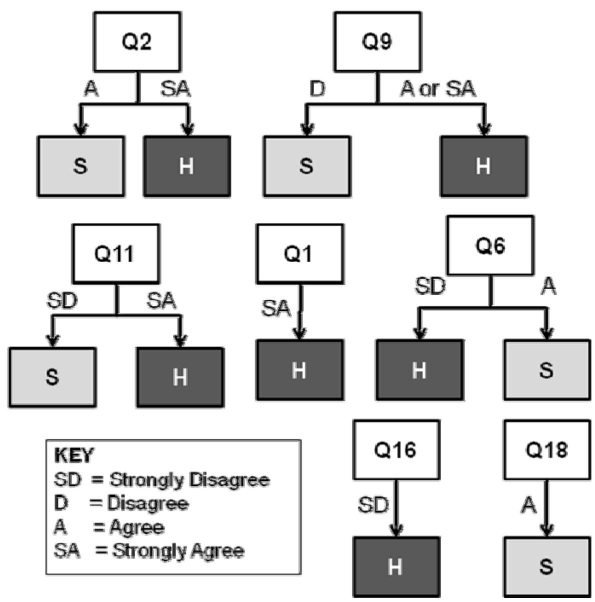

Figure 2: CN2 Decision Tree for the most accurate feature set (NN/KNN)

The results of these three features indicate that Serialists and Holists have different preferences for their navigational styles. The former prefer to follow a linear pattern by having a suggested route or looking at the subject content step-by step with back/forward buttons. Conversely, the latter tend to take a non-linear pattern by 'jumping' between different levels of subject contents with hypertext links (Jonassen and Grabowski, 1993) so they find it difficult to follow a sequential method to locate information with back/forward buttons. This is in agreement with previous literature as Serialists prefer to be given a suggested browsing pattern to direct them while Holists generally tend to use a complex linking system to find their own way (Ford et al, 1999).

The aforementioned findings demonstrate that Holists and Serialsts have different preferences for the design of the WBI program. However, they share a similar preference for Q2. If a learner strongly agrees that the examples given in this tutorial are not practical, they can be a Holist or Serialist. In other words, both types of learners consider that the examples need to be more practical. This is probably because practical examples can help them transfer knowledge into an activity (Ford & Chen, 2000). Thus, providing a concrete example may be a useful way to enhance student learning within WBI, regardless of whether they are Holists or Serialists.

Converting the Decision Tree into Decision Rules

Table 5 shows the list of rules converted from the chosen decision tree in Figure 2. As shown in this table, different rules are associated with the responses of different cognitive styles and each cognitive style is associated with more than one rule. There are six rules for Holists and five rules for Serialists. These rules can be applied to automatically suggest a student's cognitive style based on his/her preferences, which could be used to support the development of personalized WBI programs that accommodate the needs of each individual.

Table 5: Decision Rules for Holists and Serialists

Cognitive Style	Decision Rule
Holist	If learner strongly agrees that it is difficult to learn the basics of HTML without the help of a person, they are Holist.
	If learner strongly agrees that the examples given in this tutorial are not practical, they are Holist.
	If learner strongly disagrees that they would have found it more helpful to be given a suggested route through the tutorial, they are Holist.
	If learner strongly agrees or agrees that it is hard to use backward/forward buttons, they are Holist.
	If the learner strongly agrees that the links provided in this tutorial helped to discover the relationships between topics, they are Holist.
	If the learner strongly disagreed to the fact that the tutorial allowed them to learn topics in any order, they are Holist.
Serialist	If learner agrees that the examples given in this tutorial are not practical, they are Serialist.
	If learner agrees that they would have found it more helpful to be given a suggested route through the tutorial, they are Serialist.
	If learner strongly disagrees that it is hard to use backward/forward buttons, they are Serialist.
	If the learner strongly disagrees that the links provided in this tutorial helped to discover the relationships between topics, they are Serialist.
	If the learner agrees that it is easy to find a route for a specific task within the index, they are Serialist.

Implications for System Design

The decision rules provided in Table 5 suggest that Holists and Serialists do demonstrate different preferences for the design of WBI programs. This implies that WBI programs should be developed to support the unique needs of each cognitive style group. More specifically, the WBI programs should offer multiple functionalities to accommodate the different needs of Holists and Serialists. In this section, we discuss some design solutions to support the needs of Holists and Serialsts.

Design for Holists

Holists felt difficult to use this WBI program without the help of a person. In other words, there is a need to provide Holists with additional human support. To address this issue, instructors can create an email list that includes all the email addresses of the students taking the same WBI program so the students can discuss their problems and share their experience with their classmates by using this email list. Additionally, Holists thought that the links can help them discover the relationships between topics so the WBI program should present rich links to them. However, rich links may increase cognitive overhead. Thus, there is a need to use annotation, which provides additional information about the destination of a link prior to selection (Hohl, Becker, and Gunzenhauser, 1996). Such annotation can work as a visual cue to help students decide whether the link should be followed with profit or should not yet be followed.

Design for Serialists

Unlike Holists, Serialists prefer to have a suggested route so backward /forward buttons may be a useful way for them to look for information sequentially. To help them find backward /forward buttons easily, these buttons should be clearly labeled and they are consistently located in a same place of every page. The other way to provide a suggested route for Serialists is direct guidance, which offers straightforward advice or instruction to guide students' actions. More specifically, the WBI programs offer a link or button which leads to a suggested page to read next (Brusilovsky and Millán, 2007). On the other hands, rich links may not be suitable to Serialists so we may need to use links hidden to restrict navigation space for them. More specifically, links hidden can help Serialists easily to identify which pages should be visited at the given moment and which should not so that they can be protected from the complexity of the unrestricted hyperspace.

Concluding Remarks

Understanding students' preferences is useful to both teaching and learning (Graf, Kinshuk, and Liu, 2009). The aim of this study was to investigate how cognitive style affects learners' preferences for the design of WBI programs. In using a data mining approach, the findings suggest that a learner's cognitive style tend to determine their preferences for the design of the WBI programs. Holist learners preferred the provision of additional teaching support in the form of a person. In addition, Holists also preferred to have hypertext links within the subject content that allowed them to find relationships between topics. On the other hand, Serialists preferred a suggested route through the subject content, the facilities of back/forward buttons and an index. However, both Holists and Serialists were found to appreciate practical examples.

The contributions of this study lie within its theory and methodology. In terms of the former, this study strengthens the understanding of the differences in preference between Holists and Serialists. However, it was very small-scaled though there is no minimum limit for the classifiers used in this study. Further work needs to be undertaken with a larger sample to provide additional evidence especially when a data mining approach is used to conduct data analyses. In terms of the latter, we do not only proposes a novel data mining approach that integrates feature selection and decision trees for effectively selecting and visualizing the most relevant features within a dataset, but also contributes to the knowledge of the differences among the six classifiers used for feature selection and those among the three decision tree algorithms applied for classification in this study. Nevertheless, only two families of classifiers and three decision tree algorithms were considered in this study. Such limited classifiers and decision tree algorithms may cause some bias. Thus, there is a need for further works to take into account more types and families of classifiers or other types of classification algorithms to enhance the effectiveness of this data mining approach.

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